Turning Data into Dollars:
Evaluating Marketing Campaign Performance for iFood!

Team Name: The Algorithm

The Problem

Main Question
What motivates customers to engage with marketing campaigns, and how can businesses increase responsiveness using customer characteristics

Business Challenge & Impact
Companies like iFood invest heavily in marketing but often lack insight into what drives customer acceptance and retention. Without data-driven understanding, resources may be wasted on ineffective strategies.

Goal: Identify demographic and behavioral factors that influence response rates to better target promotions and improve marketing efficiency.

The Data

Source: Simulated dataset created by iFood's internal analytics team for hiring purposes.

Population: Represents customers across Brazil who interacted with iFood's promotional campaigns.

Why This Data: Offers a rich mix of demographics, spending habits, and channel usage, which is ideal for analyzing campaign response behavior.

Limitations:

1. Simulated data may not fully reflect real-world behavior.
2. Outdated (last updated in 2020), possibly missing recent consumer trends.
3. Lacks time-series elements like seasonality or changes over time.

Hypothesis/ Research Question

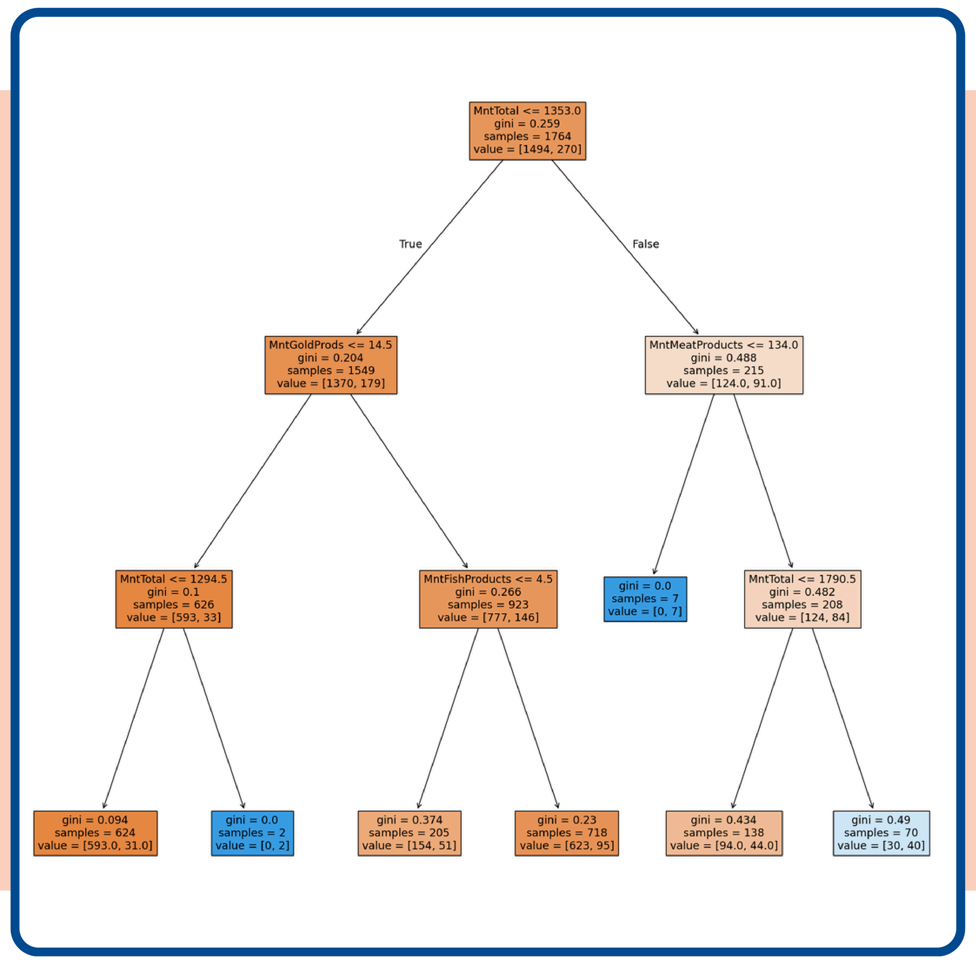
Research Question
Can we predict a customer's likelihood of responding to a marketing campaign based on their spending habits and shopping behavior?

Hypothesis
Customers who spend more on premium categories (like wine and gold products) are more likely to engage with promotional offers.

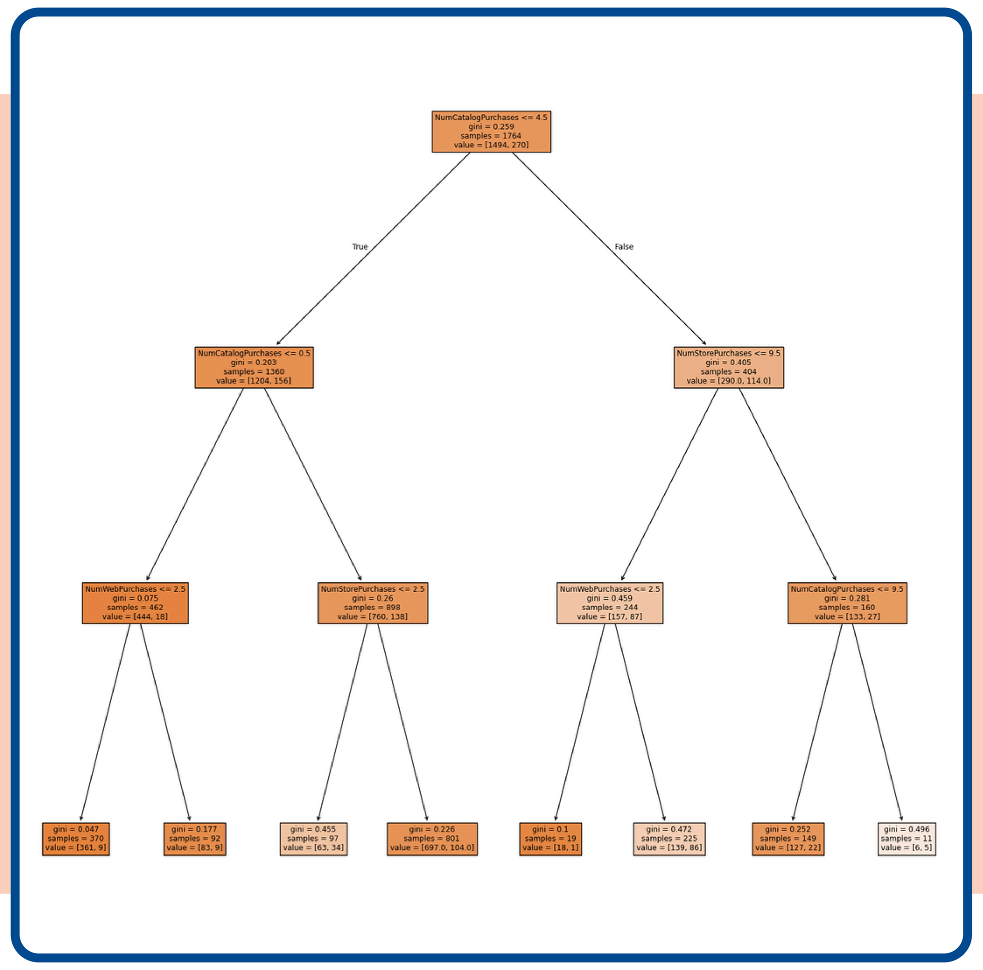
Customers who frequently shop online or take advantage of deals are more receptive to digital campaigns.

Rationale
1. Behavior > demographics
2. Smarter targeting
3. Reduce wasted spend

The Model



Spending-Based Model



Channel-Based Model

To predict whether a customer would respond to a marketing campaign, we built two shallow decision tree classifiers (depth = 3). One model focused on what customers buy (spending-based), and the other on how they shop (channel-based). Decision trees were chosen for their interpretability, ability to capture non-linear relationships, and usefulness in generating clear rules that marketing teams can act on.

The spending model split first on wine purchases, showing that premium product spend was a strong indicator of responsiveness. The channel model split first on web purchases, revealing that online, deal-seeking customers were more likely to engage with promotions. These models allow iFood to tailor outreach based on observed customer behavior.

Model Evaluation

Key Takeaways:

- Premium spenders and online deal-seekers are most responsive
- Spending behavior and shopping channels both predict campaign acceptance
- Simple, interpretable models with (depth = 3) worked well
- Class imbalance remains a challenge, so future models could use SMOTE or weighting
- Insights can directly inform iFood's real-time marketing strategies

Evaluation Method: 80/20 stratified train-test split with fixed random state

Spending-Based Model:
- 85.8% training accuracy, 85.5% test accuracy → minimal overfitting
- Root split: Wine spending over $325
- Other key splits: Gold and meat product spending

Channel-Based Model:
- 84.7% training accuracy, 85.7% test accuracy → strong generalization
- Root split: More than 4 web purchases
- Follow-up splits: Deal purchases and catalog usage

Baseline Comparison: Dummy classifier predicting "no" achieves ~85% accuracy→ Precision and recall improved, but class imbalance remains a challenge

Model Choice Justification:
- Depth-vs-accuracy analysis confirmed depth=3 offers the best trade-off
- Confusion matrix and F1-scores show room for improvement with advanced techniques